

# An Evolutionary Approach for Fusion of Active and Passive Sonar Contact Information

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*Abstract – The core problem for networked systems for underwater surveillance revolves around the requirement to blend information from different sensors and platforms into a common operating picture. Data fusion of disparate data types can be problematic given the variety of potential surveillance systems in the network. Active and passive sonar in particular provide different data types with different accuracies. The acoustic environment is highly stochastic and errors are prevalent that can be promulgated throughout the system. An evolutionary algorithm approach for fusing active and passive sonar contact information is used to explore the issue of robustness when large contact errors prevail from multiple platforms. The algorithm may have the ability to recover from erroneous input at the expense of lower track accuracy. This may have a significant utility as an operator aid for construction of the global picture of fused active and passive data. A multitude of erroneous sources can still result in higher overall track errors and further research is required; however, the evolutionary approach may still provide significant benefit.*

**Keywords:** Tracking, evolutionary algorithms, active and passive data fusion.

## 1 Introduction

Networked underwater warfare offers a significant potential for enhancement of the ability of underwater surveillance systems to detect and classify both underwater and surface contacts. Numerous sensors and platforms offer greater potential for minimizing the errors associated with contacts that are caused by the high variability of the acoustic environment. From an operations research perspective, studies have shown that this variability makes determination of the exact positions of contacts an almost impossible task in some conditions, and a stochastic approach is usually the only way of providing performance predictions of sonar systems.

Given the large variance in expected errors produced by sensors, the problem of combining the information from different surveillance platforms into one common operating picture is a challenging task. This task is complicated further by the use of different sensors having

different characteristics and outputs. At any given time the accuracy of the information obtained from one sensor may be more accurate or considerably worse than another sensor, but discrimination of which sensor is providing contact information closer to the “ground truth”, or the actual contact’s motion vector is difficult due to this variability.

For active and passive sonar in particular, active data has the ability to provide both a range and bearing to a contact. Passive data, on the other hand, only provides bearing information. It is often assumed that the active contact data will be most accurate, yet many cases can be cited where this was not the case, particularly in a high clutter environment where many false returns are obtained from bottom features or other anomalies. In these circumstances passive contact data may provide more reliable information but may be more difficult to obtain.

One approach to overcoming many of the obstacles associated with data fusion is simply to construct a graphical user interface that presents all the current data as icons to the operator. The operator can process the information and judge what contact information is accurate and based on historical data determine by observation where the target is most likely to be given the latest data. Another approach is to devise automatic tracking algorithms that provide cues as a decision aid for the operator. Tracking algorithms have a history of use.

### 1.1 Evolutionary Algorithms for Tracking

The use of evolutionary or genetic algorithms for tracking is not without precedent. Recently at DRDC Atlantic some work was conducted on a genetic algorithm tracker given active contact data only [1].

The ability of genetic algorithms to provide robust solutions for global optimization is well documented. Genetic algorithms (GA) have been used for numerous types of engineering optimization problems [2]. Genetic algorithms have been used in different ways for data fusion problems including the optimization of parameters for tracking algorithms and optimization of the bandwidth for selection of a priori observations. However, in

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general, algorithms for tracking algorithms have focused more on using Kalman filters and associated methods for conducting TMA.

The tracking algorithm problem is only one issue concerning production of a data fusion generated Common Operating Picture (COP) with respect to multi-sensor multi-platform networks. From a purely physics based perspective, the sharing of contact data between platforms that are only using a 2-D co-ordinate system vice a 3-D system leads to errors that are promulgated through the network [3]. Issues concerning human factors and “vigilance decrement” associated with operators spending hours looking at sonograms are another area of potential error that has been examined by human factors experts [4].

However the biggest probable cause of error in acoustic contact reports lies with the environment. Environment and geographical conditions in addition to oceanographic features lead to significant problems especially when operating in littoral environments. On any given day environmental conditions can result in poor sensor performance.

These operational issues lend even more importance to the ability of the networked system to be able to compensate for the multitude of errors imposed upon it during real operations. For the generation of a COP, the quality, accuracy, and robustness of the system to deal with real operational problems becomes paramount, and a system that is put forward to conduct the processing for the COP must incorporate elements to reduce, mitigate or in some cases eliminate system input errors when the situation requires less fidelity rather than more.

Using TMA programs can solve some but not all of these issues, as the case of garbage in/garbage out cannot be completely eradicated despite the best filters and the most precise techniques. This means that the challenge to find tools to manage the data fusion process rather than by solving the tracking problem need to be more closely linked. In the next sections, some examples are shown of the use of the evolutionary multi objective algorithm for doing one element of this process.

The acoustic data fusion process and the elements of various data fusion sonar systems can be analyzed from a multi-sensor fusion or a multi sensor integration perspective. It should be noted that different system characteristics may be considered multi-sensor and more distinguishing characteristics are required. For example, from computer science homogenous and heterogeneous computer systems are one way of looking at the physical system components. Topics on multi-sensor fusion have matured and textbooks are available [5]. This paper is concerned with the problem of dealing with gross errors in contact data and the use of a Multiple Objective Genetic Algorithm (MOGA) approach to the problem.

## 2 Passive and Active Fusion

The accepted definitions for passive and active sensors are generally well known but can be reiterated here. The passive sensor is said to record information already present in its surroundings or environment while the active sensor initiates an action whose response results in information recorded by the sensor. In other words, the active sensor introduces a disturbance, energy or new factor into the environment as a stimulus and checks the response, while the passive sensor measures the environment without changing it.

These traits are also representative in general of acoustic sonar systems. Division of sonar systems into passive and active present the designer with a range of options for sonar development that only became obscured as sonars were developed that combine both active and passive sensors into one system. However, the differentiation between active and passive is still used almost universally as the action required by the sonar is either active or passive.

While the current focus is on integration of active and passive sonar systems, development of underwater systems that use information from non-acoustic sensors is also being explored.

With all these systems, the integration of sensor information into one data structure is a common requirement. These systems are mostly still within the realm of a homogenous system despite the different sensors involved because the systems are developed with this purpose as part of their design. In the case of the networked underwater surveillance system, the use of multiple platforms, as well as multiple sensors means that system architecture and system characteristics are no longer uniform and this type of system is more heterogeneous.

Figure 1 shows a picture of the networked underwater warfare concept. In the figure are representative platforms including aircraft, surface ships and submarines. Each type of platform has a different sensor system albeit active or passive acoustic sonar. Producing a COP from these disparate types of sensors is difficult and complicated by the fact that each system has a different availability, reliability and accuracy. The information data exchange requirements and the project outline is described in various other references [6,7].

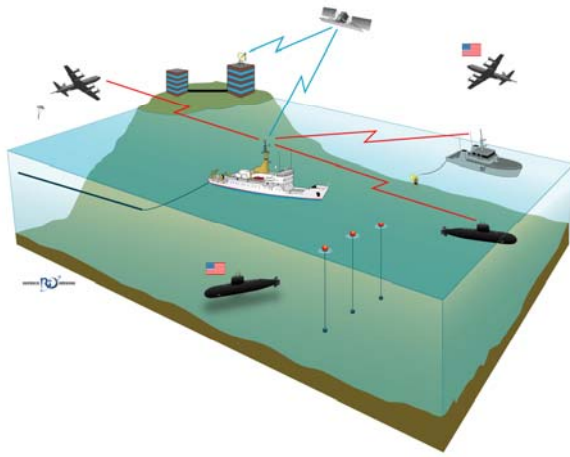


Figure 1: Networked Underwater Warfare Concept

### 3 MOGA Methodology

The algorithm used in the current study is based upon a form of MOGA that does not require a definition of Pareto optimality. Normally, a two-objective function will require some form of compromise between the objectives and as such a reduction in one objective leads to an increase in the other objective and vice versa. Such types of multiple objective functions lead to a definition of a Pareto front derived from non-dominated solutions [2].

The current algorithm still requires a definition of optimality to be able to output the current optimum, however, the algorithm itself is not based directly of the selection of optimal candidates based on non-dominated solutions. In this case the algorithm is said to be of a compromised or preferred solution rather than a technique to derive all non-dominated solutions. The current algorithm is quite effective in determining non-dominated solutions, however, the primary assumption is that the best solution is one that is best or nearly optimal in all objectives.

The algorithm is called the Sequential Objective Evolutionary Algorithm (SOEA) and was originally developed for hull form optimization of ships [8]. It has been applied to a number of other applications. The current application represents an attempt to use the characteristics of genetic algorithms to maintain a possible population of solutions that are updated as sonar contacts are received. The program works as follows. For a given initial number of ships and submarines, tracks are randomly generated which are, for the purposes of the current application, straight-line tracks. During the duration of the tracks, contacts are randomly generated from each platform against the target. Contacts can be either passive or active and are again randomly generated.

The contacts are then evaluated by the MOGA. The MOGA maintains a population of 100 initial solutions. The probability for cross-over was set at 0.8 and the mutation probability was set at 0.001, though these

parameters as for most MOGA programs can be adjusted by trial and error. For each time step, if there is a contact by a platform the algorithm is called. The algorithm uses as input the “ownship” position that is the position of the platform that has the contact, and also either the estimated  $x$  and  $y$  position of the contact or the bearing to the contact. The  $x$  and  $y$  positional information represents an active contact, while the bearing only information represents a passive contact.

In addition, the MOGA should be informed as to whether a new track is required or whether a track is being updated. A new track means the MOGA starts with a new randomly generated initial population. Except for the first contact where a new population must be generated, all of the cases presented start with the population generated after assessing the last contact.

The MOGA is run for 1000 generations. While running, the first objective to be evaluated is to minimize the error from solutions in the population between the bearings generated from the ownship to the contact. Those members of the population that have a minimal error in bearing are considered more optimal than those that have larger bearing errors.

If the contact is active, then the range between the estimated contact position and the member of the population is used as a measure of the error in track versus contact position. This objective represents the minimization of the active position error. As previously mentioned the same population is used in both active and passive cases.

In addition to minimization of the contact error, the next objective to be evaluated is to minimize the position of the GA population and the expected position. The expected position is the one generated from a vector produced from two previous optimal solutions. A diagram of the algorithm is shown in Figure 2.

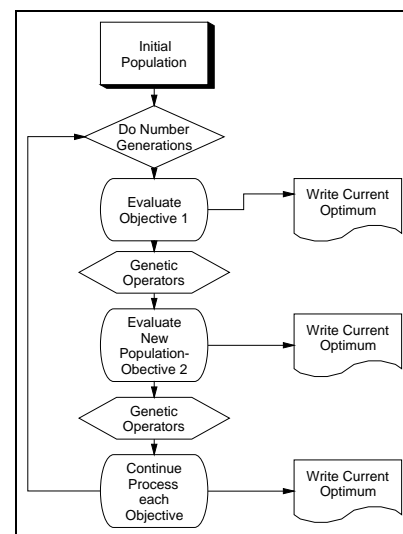


Figure 2: MOGA Algorithm

## 4 MOGA Results

In this section some results of using the MOGA approach for tracking active and passive sonar contacts are shown. It should be emphasized that the point of using this method is not necessarily to obtain a better tracking solution, but to investigate whether a more robust method can be found that can accommodate large errors in track data. That is, the goal is to be able to use both active and passive data when the data is both corrupt, error prone and completely false as well as when contacts are accurate.

For the case of a single ship versus a single target, in which the ship has both a mixture of active and passive contacts, the population of solutions generated by the MOGA are shown in Figure 3. The contact data is error free and is represented for passive bearings by end-points in the direction of the contact from the ship position to simplify the illustration. The active contacts are given by X's centred over the submarine track. As can be seen by the GA solutions at each time step represented by the circles, the accuracy of individual points from the GA solution vary somewhat, but the optimal solutions for the track positions centre around the target.

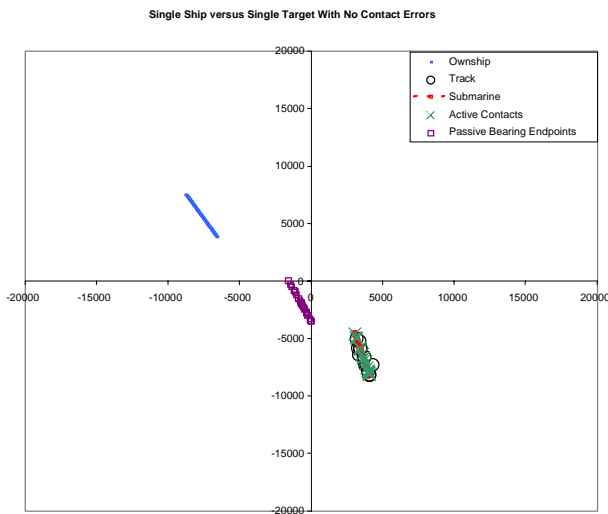


Figure 3: Single Ship vs. One Target, No Contacts Errors

For the case where there are passive contact errors by the addition of a  $\pm 10\%$  bearing error in addition to active contact error of  $\pm 10\%$  range error, the results of using the GA tracker are shown in Figure 4. In this case, the track results are less accurate but still in the region of the submarine track.

It should be noted that the track is not a continuous track but a series of optimal position estimates as provided by the algorithm when given either a new active contact or a new bearing update. This differs from the definition of a track requiring a target position as well as a target velocity and heading. In this case the track estimate is in reality a series of updated contact positions and not a "track" in the true sense.

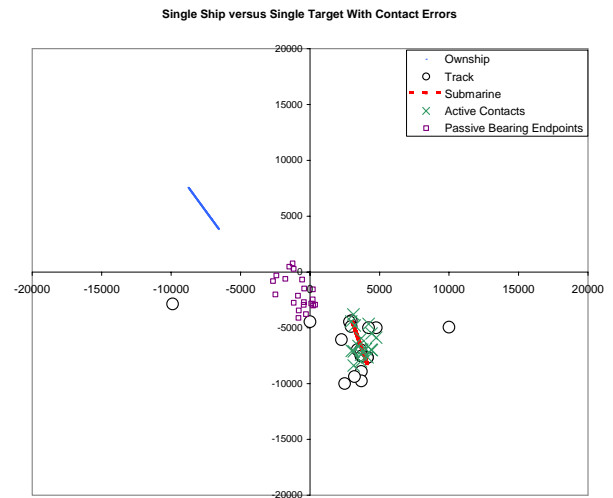


Figure 4: Single Ship vs. One Target with Contact Errors

With regard to two ships, a similar situation exists if the contact data has no error as shown in Figure 5. In this case there is more variance in the track rather than the expected higher accuracy given by two ships reports as the solution tries to find the best position according to the contacts from first one and then the other platform. The GA track is near the actual track but is not entirely accurate and some anomalies are observed. Nevertheless, the two types of both active and passive data are being incorporated into one COP of contacts by minimizing the difference associated with the population members and the contact data from two platforms as well as to types of sensors resulting in a multi-platform, multi-sensor data fusion.

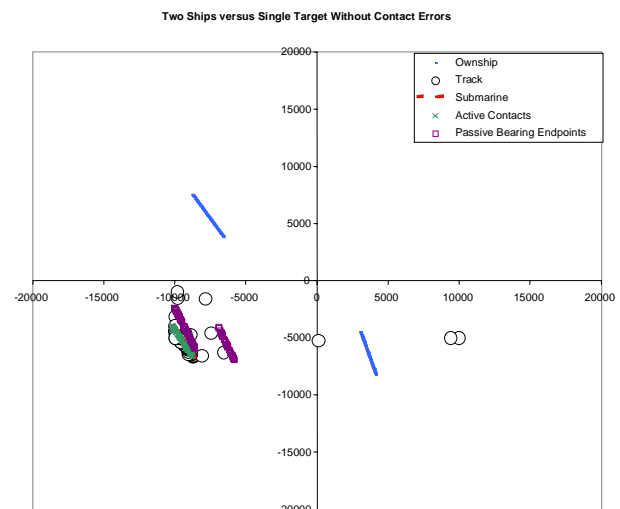


Figure 5: Two Ships vs. One Target, No Contacts Errors

For the case of two ships in which there are contact errors for both the passive and active contacts, the results of using the GA approach are shown in Figure 6. The series of track contacts are shown to be in the region of the submarine track despite the errors that are introduced by both the passive bearings and the active contacts from both platforms. It should be noted that these errors are randomly generated within the accuracies prescribed whereas most errors would be Gaussian distributed and less inaccurate.

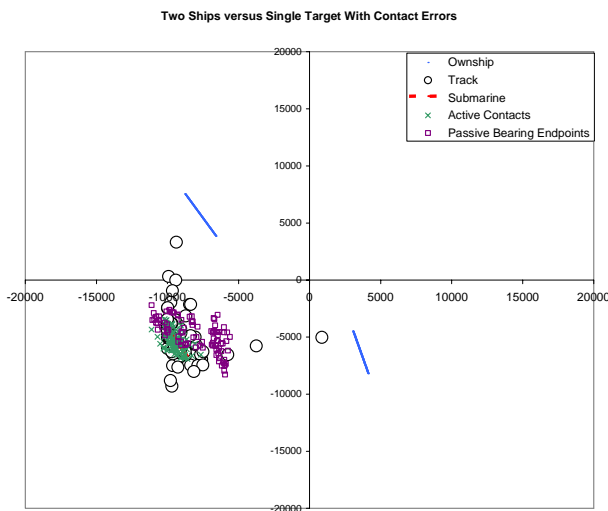


Figure 6: Two Ships vs. One Target, with Contact Errors

While the previous two cases of single platform multi-sensor error and multi-platform error were randomly generated, these errors are relative to the actual submarine position. The addition of false contacts or “clutter” is not based on the submarine position. False contacts form a large part of the errors associated with real trials. As previously mentioned, dealing with false contacts is a difficult problem from the perspective of how a tracking algorithm can provide a robust solution despite the addition of large errors due to invalid contacts.

An initial approach to dealing with false contacts is to simply filter outliers and not use the false contact data in the first place. While this approach has obvious merit, it assumes that false contacts will be correctly classified despite the fact that the false contacts *may in fact be true contacts* while the track being generated *may indeed be false*. This difficulty with discrimination of input is not easily justified and reliance of operator experience is often used to discard unwanted tracks and false data.

In addition to the errors associated with the sensor accuracies, a number of intermittent false contacts are introduced. False contacts are generated such that approximately 10% of the contacts are invalid. These are uniformly distributed within the operating region and can either be false active contacts, or invalid passive bearings. As shown in Figure 7, although there are obvious anomalies where the estimated track position corresponds

with a false active contact, the majority of contacts remain close to the submarine track.

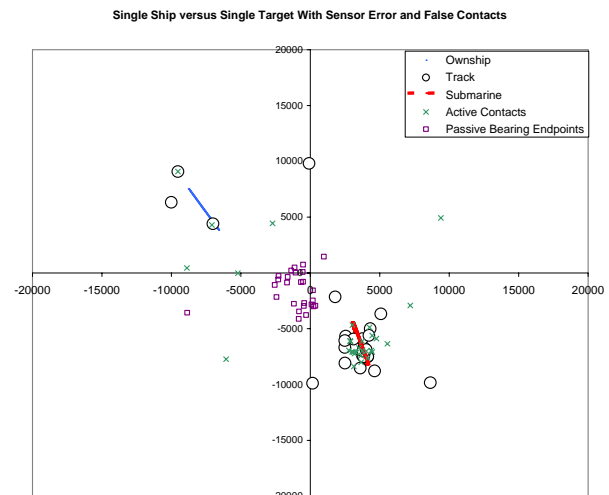


Figure 7: One Ship vs. One Target with 10% False Contacts

This is also shown for the case of two ships versus 1 target in Figure 8. For the situation where there is an increasing amount of error and an increasing amount of false contacts or clutter, the track starts to show more anomalies. For example, Figure 10 shows the situation when 50% of the contacts are false.

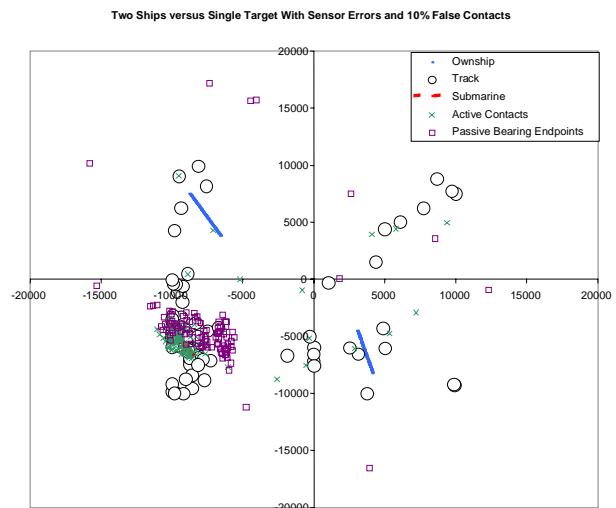


Figure 8: Two Ships vs. One Target with False Contacts

Although it is apparent that the increase in clutter has made the picture more confused, in fact the estimated contact optimal position results shown in Figure 8 clearly indicates where the submarine track is more likely to be. At this point, Kalman filters or other techniques to estimate of the most likely position of the target could be utilized to produce a track from the optimal position estimates provided by the MOGA algorithm.

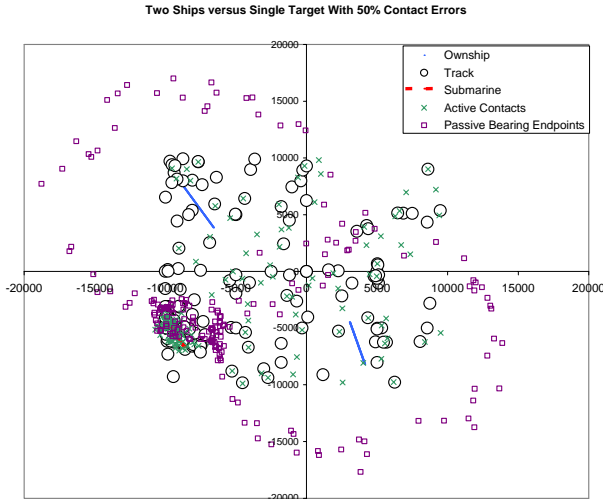


Figure 9: Two Ships vs. One Target - 50% False Contacts

One way to improve the previous results from Figure 9 could be to use a better method for predicting the expected position. As this is one of the objectives used in the MOGA for minimizing the error between the population of solutions and the expected position, a more sophisticated method for predicting the expected position should lead to a better overall result. The method used in the previous results calculates an expected position based on the last two known optimal results. This means that large inaccuracies from one or both of the previous optimal results will be promulgated as an error in prediction of the next result. This is mitigated somewhat by the actual contacts which lead the population back to a better prediction

Using a least squares method to predict, for the case of a straight-line target, a linear best-fit equation based on the cumulative history of the optimal results leads to the results shown in Figure 10 for the previous two ship case.

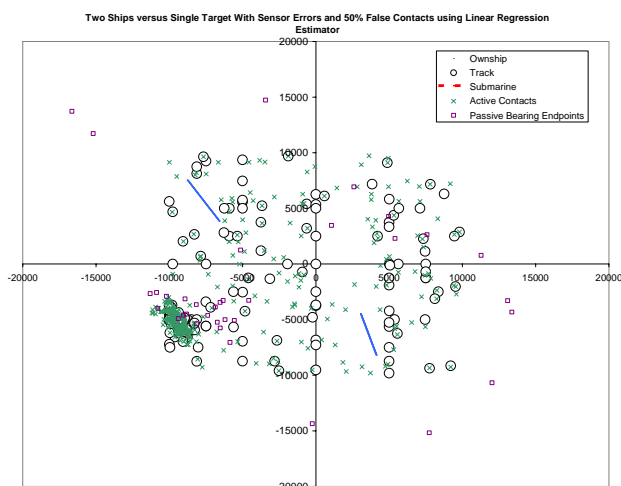


Figure 10: Two Ships vs. One Target- 50% False Contacts using a Linear Regression Estimator

## 5 Conclusions

A MOGA approach for conducting data fusion of active and passive contacts is presented. As more errors are incorporated into contact data, robust methods are required that can deal with real system input. For sonar contact data where high variability in the environment can produce large errors, the ability to maintain at least an indication of the target location is of significant operational benefit.

The MOGA approach is able to indicate general target position. Future work may compare with classical TMA techniques. The MOGA approach has proven useful in other types of applications requiring a robust methodology for global optimization. The MOGA approach minimizes errors in passive bearing only and active positional data, as one means of producing a COP. Although a simple linear regression estimate for obtaining the expected position was tested, other techniques should be investigated further as a means of reducing anomalies in the track.

The current study presents one way of using evolutionary algorithms for data fusion. Future work would employ the methodology with real operational data rather than simulated. The initial results indicate that this approach may be worth investigating as one means to augment TMA tools available to an operator.

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